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Colour Constancy for Image of Non-Uniformly Lit Scenes

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Abstract—This paper presents a colour constancy algorithm for images of scenes lit by non-uniform light sources. The proposed method determines number of colour regions within the image using a histogram-based algorithm. It then applies the K-means++ algorithm on the input image, dividing the image into its segments. The proposed algorithm computes the normalized average absolute difference (NAAD) for each segment's coefficients and uses it as a measure to determine if the segment's coefficients have sufficient colour variations. The initial colour constancy adjustment factors for each segment with sufficient colour variation is calculated based on the principle that the average values of colour components of the image are achromatic. The colour constancy adjustment weighting factors (CCAWF) for each pixel of image are determined by fusing the CCAWFs of the segments' with sufficient colour variations, weighted by their normalized Euclidian distance of the pixel from the center of the segments. Experimental results were generated using both indoor and outdoor benchmark images from the scene illuminated by single or multiple illuminants. Results show that the proposed method outperforms the state of the art techniques subjectively and objectively.

Index Terms— colour constancy, multi-illuminants, k-means segmentation, fusion

I. INTRODUCTION

The human colour perception system has the capability to perceive the colour of an object as relatively constant regardless of the colour of the source illuminant. However, the colour constancy mechanism of the human visual system is not understood well enough to create a computational model in the image processing pipeline [1]. The appearance of a digital image depends on the prevailing illuminant, reflection property of the objects and the camera sensitivity function [2]. Hence, the true colours of objects within a scene of a digital image are often changed by the colour of present light sources. This is seen as a colour cast in the image [3]. The main aim of colour constancy algorithms is to remove the colour cast from digital images due to the colour of scene illuminants [4].

Related Work

Researchers have proposed a considerable number of colour constancy algorithms over the past three decades [5-13, 16, 17, 22, 23]. In this section, the key colour constancy adjustment methods are discussed. The Grey World [5], the Max-RGB [6] and the Shades of Grey [7] are the main statistical based colour constancy methods. These techniques are based on some assumptions on the statistics of the image data. Van de Weijer *et al.* [8] proposed the Grey Edge hypothesis, which assumes that the average edge difference of a scene's image data is achromatic. The authors developed a framework that unified all the above-named methods. The

framework is shown in equation (1):

$$\left(\int \left| \frac{\partial^n f_{c,\sigma}(x)}{\partial x^n} \right| dx \right)^{1/p} = k e_c^{n,p,\sigma} \quad (1)$$

Where $|\cdot|$ indicates the Forbenius norm, c is the image colour component and $c = \{R, G, B\}$, n is the order of the derivative, p is the Minkowski-norm, and $f_{c,\sigma} = f_c \times G_\sigma$ is the convolution of the image with a Gaussian filter with scale parameter σ .

Equation (1) can be used to represent different statistical colour constancy algorithms by using various values of p . For $p = 1$ equation (1) becomes the Grey World method, which assumes the average value of all colour components within an image are achromatic. If $p = \infty$, equation (1) represents the Max-RGB colour constancy algorithm, which assumes that the maximum values of the image colour components are achromatic. By setting p to 6, equation (1) becomes the Shades of Gray algorithm, which has less data dependency than the Gray World and White Patch colour correction methods. Equation (1) can also represent higher order colour constancy methods such as Grey Edge-1 and Grey Edge-2 by setting $p = 1$, $\sigma = 1$ and $n = 1$ or 2, respectively. These two approaches are based on the assumption that image colour components' derivatives are achromatic.

The Weighted Grey Edge method was proposed by Gisenji *et al.* in [9]. This colour balancing approach is an extension of the Grey Edge algorithm, which incorporates the general weighting scheme of the Grey Edge method and the edge of the shadows within the image to achieve colour correction. A moment-based colour balancing method, which uses several higher order moments of the colour features on a fixed 3×3 matrix transformation, was introduced by Finlayson in [10].

Learning-based colour constancy adjustment methods have recently reported in the literature. The colour constancy problem as a 2D spatial localization task in a log-chrominance space was formulated by Baron in [11]. Baron observed that scaling the image colour components induces a translation in the log-chromaticity histogram of the image. This allows the colour constancy problem to be approached using tools Convolutional Neural Network (CNN). A light source estimation algorithm, which employs a CNN that contains one convolutional layer, one fully connected neural network layer and three output nodes, was proposed in [12] by Bianco *et al.* The CNN based technique samples multiple non-overlapping patches of the input image and then applies a histogram-stretching algorithm to neutralize the contrast of the image. It then fuses the patch scores, which are obtained by extracting activation values of the last hidden layer to guess the light source. They reported satisfactory

performance of the algorithm on a specific raw image dataset. An extension of the neural-network-based colour correction method was introduced by Fourure *et al.* in [13]. This algorithm uses a mix-pooling method to determine the availability of accurate features to be learned for the colour balancing technique. Most of the aforementioned algorithms work reasonable well when there the scene is illuminated by a uniform light source and in the absence of big uniform colour areas within the image, but the performance of existing algorithms is deteriorated in the presence of large uniform colour areas and when scene is illuminated by multiple non-uniform light colour sources.

This paper introduces a colour constancy algorithm for images of scenes lit by non-uniform light sources. The proposed algorithm uses a histogram-based approach to determine the number segments to reasonable represent different colour patch variations of the image. The K-means⁺⁺ clustering method [14] then takes this number and splits the input image into this number of segments based on its colour variation. The proposed method then computes the Normalized Average Absolute Difference for each resulting segment and uses it as a criterion to discard segments representing uniform colour areas which could potentially bias the colour-balanced image toward the colour of the big uniform colour area of the image. The initial colour constancy adjustment weighting factors for each of the remaining segments are computed based on the principle that the achromatic values of the colour components are neutral. The colour constancy adjustment weighting factors for each pixel are finally determined by fusing the colour constancy of all selected segments adjusted by the normalized Euclidian distance of the pixel from the centroids of the selected segments. Experimental results on the images of benchmark standard image datasets show the merit of the proposed algorithm over existing techniques. The rest of this paper is organized as follows: In Section II, the proposed algorithm is described, experimental results and their evaluation are given in Section III and Section IV concludes the paper.

II. IMAGE COLOUR CONSTANCY ADJUSTMENT BY FUSION OF IMAGE SEGMENTS' INITIAL COLOUR CORRECTION FACTORS

The proposed Colour Constancy Adjustment by Fusion of Image Segments' initial colour correction factors (CCAFIS) algorithm can be divided into three steps: automatic image segmentation, segments' selection and calculation of initial colour constancy weighting factors for each segment and calculation of the colour adjustment factors for each pixel by fusing the initial weighting factors of the selected segments. These three steps are detailed in the following sub-sections.

2.1 Automatic image segmentation

The proposed automatic image segmentation algorithm converts the input RGB image into a grey image. It then split the coefficient within the resulting grey image into a histogram with 256 bins. The algorithm smooths the resulting histogram by six time filtering it using the following Gaussian low-pass filter:

$$\begin{matrix} 0.25 & 0.50 & 0.25 \end{matrix}$$

It then counts the number of the local maxima within the smoothed histogram to determine the required number of the segments for the proposed colour constancy algorithm. To do this, the minimum distance between two local maxima and

the minimum local maxima height were set to 0.05 and 0.001th of the total number of image pixels, respectively. The calculated number of segments and the L a*b* format of the input RGB image are then fed into a K-means⁺⁺ algorithm. The K-means⁺⁺ clustering algorithm divides the input image pixels into a number of segments based on their colour properties.

2.2 Segments' selection and calculation of initial colour constancy weighting factors for each segment

In this section, each of the resulting segments are processed independently to circumvent the segments containing uniform areas and to calculate initial colour adjustment factors for each segment, as follows:

It calculates the Normalized Average Absolute Difference (NAAD) for each colour component of the segment using equation (2):

$$NAAD_C = \left\{ \frac{1}{T \times \bar{F}_C} \sum_{x,y \in segment} (|F_C(x,y) - \bar{F}_C|) \right\} \quad (2)$$

where $NAAD_C$ is the Normalized Average Absolute Difference of the segments colour component C , $C \in \{R, G, B\}$, T is the total number of pixels in the segment, $F_C(x,y)$ represents component C 's coefficients of the segment at location x and y and \bar{F}_C is the average value of the component C of the segment's coefficients.

The resulting $NAAD_C$ value is compared with an empirically pre-determined threshold value for that colour component. Threshold value for colour component R , G and B are named T_R , T_G and T_B , respectively. If the calculated $NAAD$ values of the three colour components of the segment are greater than their respective threshold values, it implies that the segment represent a non-uniform colour area. Hence, this segment is selected to contribute to the colour correction of the whole image and a bit representing this segment within the Decision Vector (DV) is set. The proposed technique then calculates the initial colour adjustment factors for the selected segment using the Grey World algorithm [5], as written in equation (3):

$$K_C = S_{mean} / S_{C_{mean}} \quad (3)$$

where K_C is component C initial colour adjustment factor, S_{mean} is the average value of the segment's coefficients, $S_{C_{mean}}$ represents the average value of the segment's component C 's coefficients, where $C \in \{R, G, B\}$.

In this research, the Grey World colour constancy method, which is one of the effective and yet less computationally expensive techniques compared to other colour constancy algorithms [4, 5], is used for simplicity to compute the initial colour constancy weighting factors for segments. However, other statistical colour constancy methods can be used.

2.3 Calculation of the colour adjustment factors for each pixel by fusing the initial weighting factors of the selected segments

In this section, the fusion of the initially calculated colour constancy adjustment factors for the selected segments to

calculate per pixel colour correction weighting factors is discussed. The calculated initial colour constancy adjustment factors of the selected segments, the gravitational centroid of each selected segment's pixels and the Decision Vector (DV) are fed to the algorithm. The proposed algorithm calculates the Euclidian distance of each pixel from the centers of the selected segments and uses them to regulate initially calculated colour adjustment factors to determine per pixel weighting factors using equation (4):

$$k_{Ci} = \frac{d_1}{d_1+d_2+\dots+d_n} (k_{C1}) + \frac{d_2}{d_1+d_2+\dots+d_n} (k_{C2}) + \dots + \frac{d_n}{d_1+d_2+\dots+d_n} (k_{Cn}) \quad (4)$$

where k_{Ci} is the colour constancy adjustment factor for component C of the pixel i , $C \in \{R, G, B\}$, d_1, d_2, \dots, d_n are the Euclidian distance of the pixel i from the centroid of the segments 1, 2, ..., n , respectively.

This balances the effect of colours of different light sources on the colour of each pixel. The resulting weighting factors are used to colour balance the input image using The Von-Kries Diagonal model [15], as shown in equation (5):

$$I_{out_i} = \begin{pmatrix} K_{Ri} & 0 & 0 \\ 0 & K_{Gi} & 0 \\ 0 & 0 & K_{Bi} \end{pmatrix} \begin{pmatrix} I_{Ri} \\ I_{Gi} \\ I_{Bi} \end{pmatrix} \quad (5)$$

where I_{out_i} is the colour balanced pixel i , K_{Ri}, K_{Gi}, K_{Bi} are the calculated weighting factors for pixel i and I_{Ri}, I_{Gi}, I_{Bi} are the R, G and B colour components of the pixel i of the input image.

III. EXPERIMENTAL RESULTS

In this section, the performance of the proposed Colour Constancy Adjustment by Fusion of Image Segments' initial colour correction factors (CCAFIS) is assessed on five benchmark image datasets, namely: Multiple Light Source (MLS) dataset [16], The multiple illuminant and multiple object (MIMO) image dataset [17], Gehler and Shi image dataset [18], Grey Ball image dataset [19] and the UPenn Natural Image dataset [20]. The Evaluation procedures are discussed in sub-section 3.1, an example of image segmentation and segment selection is shown in sub-section 3.2 and the experimental results are discussed in sub-section 3.3.

3.1 Evaluation procedure

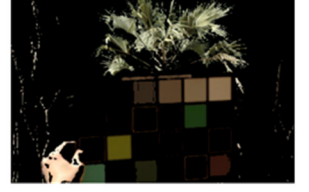
The performance of the colour constancy algorithms are usually assessed both objectively and subjectively. Angular error is an objective criterion that is widely used to assess the colour constancy of the images which measures the distance between the colour corrected image and its ground truth. A lower mean or median angular error of the images of an algorithm indicates that the algorithm's performance is superior. The angular error of an image can be calculated using equation (6):



(a)



(b)



(c)



(d)



(e)

Fig.1. A sample image from the UPenn dataset and its four resulting segments: (a) original image, (b-e) segment 1-4.

TABLE I
NORMALISED AVERAGE ABSOLUTE DIFFERENCE (NAAD)
VALUES OF DIFFERENT COLOUR COMPONENTS OF THE IMAGE
SEGMENTS

Segments NAAD	segment 1	segment 2	segment 3	segment 4
R_{NAAD}	0.37	0.49	0.04	0.26
G_{NAAD}	0.39	0.28	0.02	0.32
B_{NAAD}	0.39	0.40	0.02	0.35

$$angular\ error = \cos^{-1}\left(\frac{e \cdot \hat{e}}{\|e\| \|\hat{e}\|}\right) \quad (6)$$

where $e \cdot \hat{e}$ shows the dot product of the ground-truth and the colour-corrected image vectors, respectively, and $\| \cdot \|$ is the Euclidian norm of the specified vector.

Since human eyes are the final judge for assessing the colour constancy of the images, subjective evaluation is considered to be the most reliable assessment method to measure the colour constancy of the images. Mean Opinion Score (MOS) is a popular subjective evaluation method which is widely used to compare the visual quality of the images. To determine the MOS score for images of different colour constancy adjustment methods, a set of images of different scenes containing diverse backgrounds and foregrounds, objects and a range of colour variations that are taken under various lighting conditions is first chosen. These images are then colour corrected using different colour balancing techniques. The resulting images are shown to observers who score the images based on their colour constancy. The MOS score of each method finally calculated by computing the average score of its images.

Objective criteria are widely used to assess the performance of different colour constancy techniques due to

its simplicity. However, there is significant debate on consistency of objective measurements with their counterpart subjective assessment. Some researchers have argued that objective measurements may not always be in agreement with the subjective quality of the image [21]. Hence, in this paper, both subjective and objective assessment methods have been used to assess the quality of the *colour* corrected images.

3.2 Example of image segmentation and segment selection

To visualize the effectiveness of the proposed method in dividing the image into a number of segments and identifying segments with uniform colour areas, a sample image from the UPenn [20] images dataset is taken and processed by the proposed method. Fig. 1a shows the input image and Fig. 1b-e show its resulting four segments, where the remaining areas of the image are shown in black, respectively.

From Fig. 1, it can be seen that Fig. 1d represent the segment with uniform *colour* areas. The Normalized Average Absolute Differences (NAAD) of the three colour components of the resulting segments have been calculated using equation (2) and tabulated in Table 1. From this table, it can be noted that the calculated NAAD values for the three colour components of segment 3, which represent the uniform colour area of the image, are below the imperially determined thresholds' values ($T_R = 0.01$, $T_G = 0.01$ and $T_B = 0.01$ for R, G and B colour components; respectively). Hence, the proposed Colour Constancy Adjustment by Fusion of Image Segments' initial colour correction factors method will exclude this segment's coefficients from contributing into the colour correction of the whole image.

3.3 Experimental results

In the next two sub-sections, subjective and objective results for the proposed method will be presented.

3.3.1 Subjective result

To demonstrate the subjective performance of the proposed Colour Constancy Adjustment by Fusion of Image Segments' initial colour correction factors (CCAFIS) method and enable the reader to compare the quality of its colour corrected images with those of the state of the art colour constancy techniques, two sample images from the Gehler and Shi [18] and the Upenn Natural Image [20] benchmark image datasets are selected and colour balance using different colour correction methods. Fig. 2 shows a sample image from the Gehler and Shi dataset, its ground truth and its colour balanced images using the Weighted Grey Edge, Corrected Moment, Cheng *et al.* [22] and the proposed CCAFIS techniques. The resulting images have also been linearly gamma corrected to improve their visual qualities. From Fig. 2a, it can be seen that the input image have a significant green colour cast where the scene is illuminated by multiple indoor and outdoor light sources. Fig. 2b shows the ground truth of the image. Fig. 2c shows the Weighted Grey Edge method's image which shows slightly lower green colour cast than the input image. Fig. 2d illustrates the Corrected Moment's image which demonstrates a yellow to orange colour cast. Cheng *et al.*'s method's image is shown in Fig. 2e. This image suffers from the extreme presence of deep yellow-orange colour cast. The proposed CCAFIS method's image, shown in Fig. 2f, exhibits the highest colour constancy and it appears to be very similar to its ground truth. The angular error of the images is also shown on the images; from these figures it can be seen that the angular error of the proposed

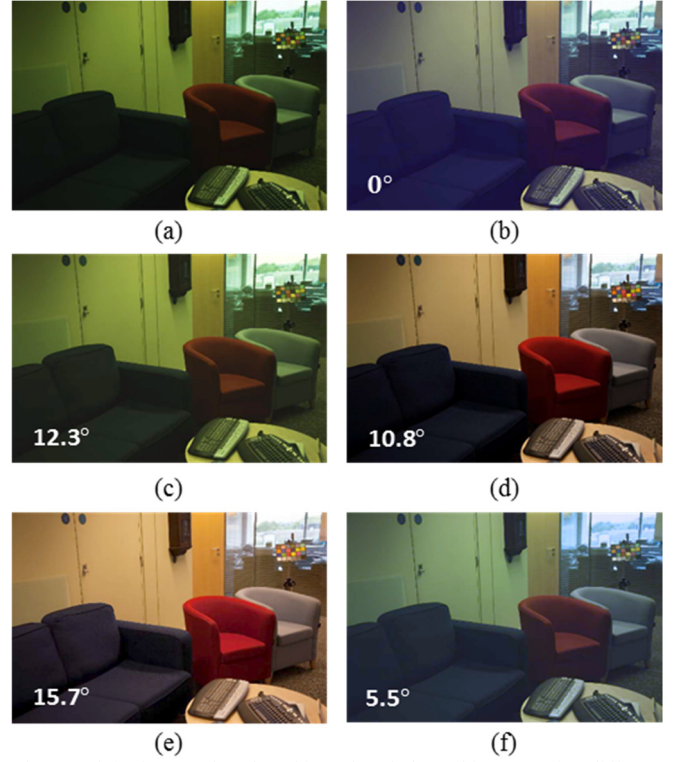


Fig. 2. Original, ground truth and its colour balanced images using different colour correction methods: (a) Original image from the Gehler and Shi dataset, (b) Ground truth image, (c) Weighted Grey Edge, (d) Corrected Moment, (e) Cheng *et al.* and (f) Proposed CCAFIS' methods' images.

method's image is the lowest amongst all other methods' images, which implies the objective qualities of the images are consistent with their subjective qualities.

Fig. 3 shows a sample image from the UPenn dataset, its ground truth and colour balance images using the Max-RGB, Shades of Grey, Grey Edge-1, Grey Edge-2, Weighted Grey Edge and the proposed CCAFIS' methods' images. From Fig. 3a, it can be seen that the input image exhibits a yellow colour cast. The tree's green leaves and the colour chart exhibit yellow colour cast. Fig. 3b is the ground truth image. Fig. 3c shows the Max-RGB method's image. From this image, it can be noted that the image have slightly higher yellow colour cast than its original input image. The Shades of Grey method's image is shown in Fig. 3d. This figure demonstrates significantly higher yellow colour cast than the original image, particularly on the tree's green leaves area of the image. Fig. 3e is the Grey Edge-1 method's image. This image also suffers from increased colour cast on the tree's green leaves and the colour chart areas of the image. The Grey Edge- method's image is shown in Fig. 3f. This image demonstrates a slightly higher colour constancy then its original image. The tree and the deciduous plants on the left side of the image have slightly lower colour cast than the original image. The Weighted Grey Edge method image is illustrated in Fig. 3g. This image appearance to be very alike to that of the Grey Edge-1 method's image, shown in Fig. 3e. Fig. 3h illustrates the proposed CCAFIS method's image, which seems as if it has been taken under canonical light. From a closer observation, it can be observed that the colour chart, the deciduous plants, the human hand and the green leaves of the tree areas of the image exhibit very high colour constancy. The colour constancy of the proposed method's image is very close to that of its ground truth. Hence, it can be concluded that the proposed method's image has the

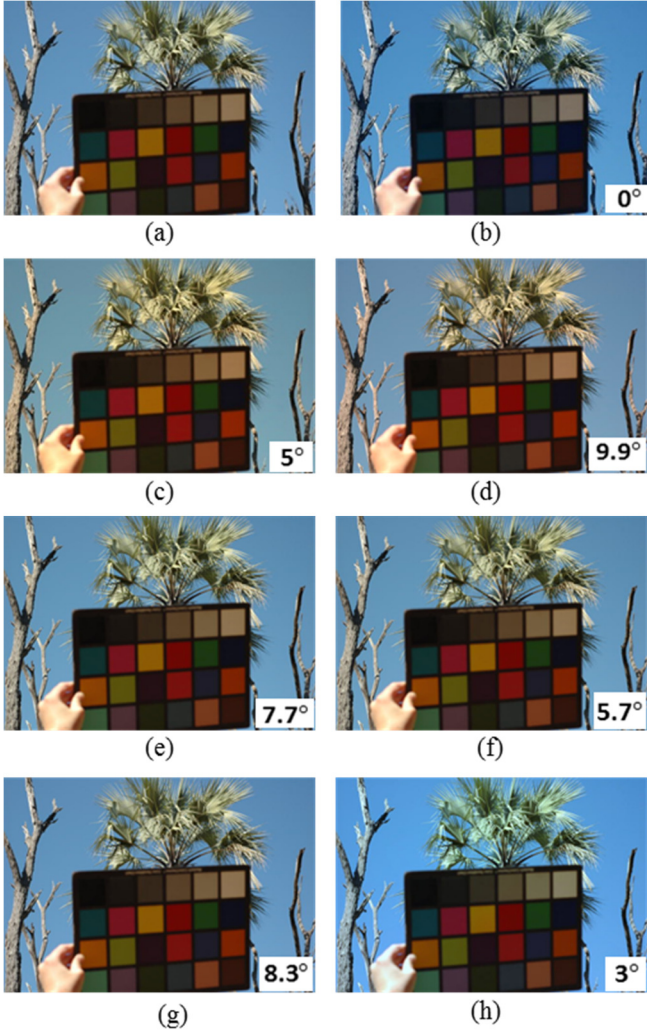


Fig. 3. Original, ground truth and its colour balanced images using different colour correction methods: (a) Original image from the UPenn dataset, (b) Ground truth, (c) Max-RGB, (d) Shades of Grey, (e) Grey Edge-1, (f) Grey Edge-2, (g) Weighted Grey Edge and (h) Proposed CCAFIS' methods' images.

highest colour constancy amongst all other techniques' images.

To generate the Mean Opinion Score (MOS) for the images of the proposed and the state of the art colour constancy methods, a set of images from the Grey Ball, Gehler and Shi and the MIMO image datasets was chosen. The selected images were colour corrected using the proposed CCAFIS and the state-of-the art techniques. Ten independent observers subjectively evaluated the resulting colour-balanced images. The viewers scored the colour constancy of each image from 1 to 5, where 1 to 5 characterize the lowest to highest colour constancy. The average MOS score of different methods' images were then calculated and tabulated in Table II. From Table II, it can be noted that the proposed method's images have the highest average MOS score in comparison to all other techniques' images. This implies that the proposed method's images have the uppermost colour constancy.

3.3.2 Objective result

To evaluate the objective performance of the proposed method, the proposed method and Grey world, Max-RGB, Grey Edge-1, Grey Edge-2, Gijsenij *et al.* [16], MIRF [17],

TABLE II
MEAN OPINION SCORE (MOS) OF THE PROPOSED AND THE STATE-OF-THE-ART TECHNIQUES

Dataset (number of images)	Method				
	WGE	Gisenji <i>et al.</i>	MIRF	Cheng <i>et al.</i>	Proposed CCAFIS
MLS (9 outdoor)	3.25	4.20	4.04	3.69	4.22
MIMO (78)	3.71	3.80	4.18	4.12	4.24
Grey Ball (200)	4.00	3.25	3.88	3.94	4.36
Gehler and Shi (100)	3.80	3.76	3.91	3.79	4.29
UPenn (57)	3.92	3.85	4.09	3.94	4.12

TABLE III
MEAN AND MEDIAN ERROR OF VARIOUS METHODS ON
IMAGES OF MIMO DATASET

Method	MIMO (real)		MIMO (lab)	
	Mean	Median	Mean	Median
Grey world	4.2°	5.2°	3.2°	2.9°
Max-RGB	5.6°	6.8°	7.8°	7.6°
Grey Edge-1	3.9°	5.3°	3.1°	2.8°
Grey Edge-2	4.7°	6.0°	3.2°	2.9°
Gijsenij <i>et al.</i>	4.2°	3.8°	4.2°	4.8°
MIRF	4.1°	3.3°	2.6°	2.6°
Grey Pixel	5.7°	3.2°	2.5°	3.1°
Proposed CCAFIS	4.2°	4.3°	2.1°	2.7°

TABLE IV
MEDIAN ANGULAR ERRORS FOR 9 OUTDOOR IMAGE OF
MULTIPLE LIGHT SOURCE DATASET

Method	Median error
Max-RGB	7.8°
Grey World	8.9°
Grey Edge-1	6.4°
Grey Edge-2	5.0°
Gisenji <i>et al.</i>	5.1°
Proposed CCAFIS	2.6°

Grey Pixel [23] methods were used to colour balance the real world and laboratory images of the MIMO dataset, as well as 9 outdoor images of the Multiple light sources dataset. The average mean and median angular errors of the colour-balanced images of MIMO image dataset for different techniques were computed and tabulated in Table III and the median angular errors for 9 outdoor image of multiple light source dataset for different algorithm were determined and tabulated in Table IV. From Table III, it can be seen that the proposed CCAFIS method's mean angular error for real world images of the MIMO dataset is 4.2°. This is the same as the Grey World's mean angular error and slightly higher than that of the Gisenji *et al.* and MIRF methods, in which their images have the smallest mean angular error of 4.1°. The median angular error of the proposed CCAFIS method is 4.3°, which is the lowest amongst all of the statistic-based methods. For the laboratory images, the proposed CCAFIS method's mean angular error is 2.1° and the median angular is 2.7° which are the lowest angular errors compared to all other methods. This implies that the proposed CCAFIS method has the highest objective performance when dealing with lab images of MIMO dataset. From Table IV, it can be noted the proposed CCAFIS method's images exhibit the lowest median angular error amongst all statistical and the

state of art techniques. This implies that the proposed CCAFIS method's capability is higher than other methods in adjusting the colour constancy of the images taken from scenes illuminated by multiple light sources.

IV. CONCLUSIONS

This paper presented a colour constancy algorithm for non-uniformly lit scenes' images. The algorithm uses the K-means⁺⁺ clustering algorithm along with a histogram-based method to divide the input image into a number of segments with similar colour variations. The normalized average absolute difference (NAAD) of the resulting segments are then calculated and used as a measure to exclude segments with uniform colour areas from being included in the calculation of colour constancy adjustment factors for the whole image. The initial colour constancy-weighting factor for each of the remaining segments were calculated using the Grey World method. The colour constancy adjustment factors for each pixel were finally computed by fusing the initial colour constancy of the remaining segments regulated by the Euclidian distances of the pixel from the centroids of all remaining segments. Experimental results on benchmark single and multiple illuminant image datasets showed that the proposed method gives significantly higher performance to those of the statistical based techniques. Moreover, the proposed techniques gave higher or very competitive results to those of non-statistical based colour constancy algorithms.

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